

# Cognitive Random Access for Internet-of-Things Networks

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**Abstract**—This paper focuses on cognitive radio (CR) internet-of-things (IoT) networks where spectrum sensors are deployed for IoT CR devices, which do not have enough hardware capability to identify an unoccupied spectrum by themselves. In this sensor-enabled IoT CR network, the CR devices and the sensors are separated. It induces that spectrum occupancies at locations of CR devices and sensors could be different. To handle this difference, we investigate a conditional interference distribution (CID) at the CR device for a given measured interference at the sensor. We can observe a spatial correlation of the aggregate interference distribution through the CID. Reflecting the CID, we devise a cognitive random access scheme which adaptively adjusts transmission probability with respect to the interference measurement of the sensor. Our scheme improves area spectral efficiency (ASE) compared to conventional ALOHA and an adaptive transmission scheme which attempts to send data when the sensor measurement is lower than an interference threshold.

**Index Terms**—Cognitive random access, dynamic spectrum access, adaptive transmission probability, internet-of-things, conditional interference distribution

## I. INTRODUCTION

The increase of wireless internet-of-things (IoT) requires a large volume of vacant frequency bands that the current dedicated spectrum policy cannot cope with. To handle the spectrum shortage, the devices need to detect and access an unoccupied spectrum in an opportunistic manner [1], [2]. However, most wireless IoT devices are hard to perform precise spectrum sensing by themselves due to their limited hardware capability and less cost [3]. Spectrum sensors are essential as a part of the infrastructure for the sole purpose of interference monitoring [4].

The locational difference of an IoT device and the corresponding sensor causes an observation error of spectrum occupancy. A mathematical model reflecting this spatial relationship is thus required. To this end, we derive a conditional interference distribution (CID) at an IoT device for a given measured interference from the sensor using stochastic geometry (SG). We find that its shape is skewed to the left of the sensor measurement and it has a long tail to the right side. This asymmetric tendency becomes intensified with increasing the measured interference level at the sensor. In other words, the IoT devices may experience less interference than the measured value with high probability. From the perspective of an opportunistic spectrum access, the IoT device would have more chances to exploit the band while guaranteeing the quality of services (QoS) of primary communications. It is worth mentioning that the existing interference distributions based on SG [5]–[8] cannot explain the above asymmetric

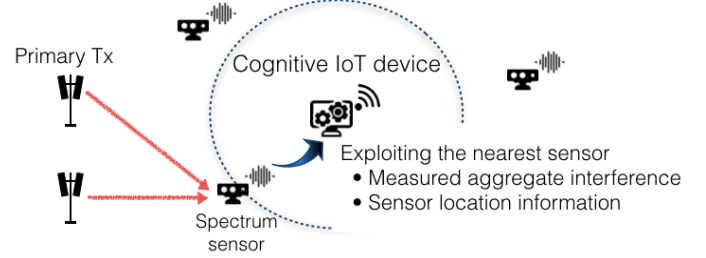


Fig. 1. Cognitive IoT networks with spectrum sensors

spatial correlation between the sensors and the IoT devices, which is a key to design cognitive radio IoT networks.

We propose a novel cognitive random access algorithm to adjust its transmission probability in a distributed manner according to the measured interference. Based on the CID, the proposed algorithm improves an area spectral efficiency (ASE) in return while satisfying the requirement of primary users. Analytic and numerical results show that our algorithm outperforms conventional ALOHA [12] and threshold based random access protocol with a hard decision, where an IoT device can access the medium only when a measured sensor value is lower than the predetermined threshold.

The rest of the paper is organized as follows. In Section II, we describe the system model and analyze the CID. In Section III, we investigate our cognitive random access scheme and verify the performance through simulations. Section IV concludes the paper.

## II. INTERFERENCE DISTRIBUTION CONDITIONING ON SENSOR MEASUREMENT

### A. System Model

In cognitive IoT networks with spectrum sensors, primary and IoT services try to access a shared spectrum band. The primary transmitter (PT) has a license to access the spectrum. The IoT transmitter, denoted as secondary transmitter (ST), may acquire opportunistic access to the spectrum by exploiting the sensor measurement as shown in Fig. 1.

Consider a pair of ST and a sensor, where the sensor is located at the center. The distance between the sensor and ST is  $d$ . The sensor and the ST are surrounded by PTs, whose locations follow a Poisson point process (PPP)  $\Phi_p = \{x_1, x_2, \dots\} \in \mathbb{R}^2$  of density  $\lambda_p$ . The locations of STs follow another independent PPP  $\Phi_s = \{y_1, y_2, \dots\} \in \mathbb{R}^2$  of density  $\lambda_s$ .

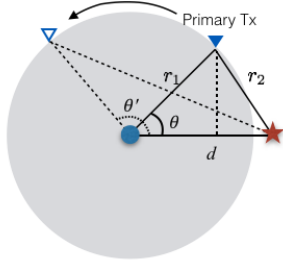


Fig. 2. Schematic diagrams including a spectrum sensor (blue circle), its nearest PT (blue triangle), and the adjacent ST (red pentagram).

PTs and STs in the network use transmission powers  $P_p$  and  $P_s$ , respectively. We consider distance-dependent path loss, where  $l(x, y) = \min\{1, \|x - y\|^{-\alpha}\}$ . Parameter  $\alpha > 2$  is a path-loss exponent. Fading is modeled as an independent and identical random variable  $h$ . Transmissions made by PUs impose an aggregate interference  $I_{\Phi_p}$  at the sensor as follows:

$$I_{\Phi_p} = \sum_{z \in \Phi_p} P_p h_z l(z, o). \quad (1)$$

In this paper, we assume that spectrum sensors use energy detection [13] and measure the aggregate interference  $I_{\Phi_p}$  without an error.

### B. Conditional Interference Distribution

We focus on an interference distribution at the point at a distance  $d$  from the sensor, when the sensor measurement  $I_m$  is given. We specify the conditional interference distribution (CID) function as

$$f_{I,m}(x) = \Pr\{I = x | I_m = m\}. \quad (2)$$

To derive the CID (2), we consider geometric situations, where PTs impose an aggregate interference to a sensor and its adjacent ST as depicted in Fig. 2. Let  $r_1$  denote the distance between a sensor and its nearest PT. The variable  $r_2$  is the distance between the PT and the corresponding ST. Two lines from the sensor to the PT and the ST form an angle  $\theta$  in radian unit.

**Proposition 1.** When a measured interference  $I_m = m$ , the CID function  $f_{I,m}(x)$  is given as:

$$f_{I,m}(x) = \frac{\frac{P_p}{\pi d \hat{r}_1 \alpha (x - T(\hat{r}_1, \alpha, \lambda_p))^2} \left( \frac{P_p}{x - T(\hat{r}_1, \alpha, \lambda_p)} \right)^{\frac{2}{\alpha} - 1}}{\sqrt{1 - \frac{\left( \hat{r}_1^2 + d^2 - \left( \frac{P_p}{x - T(\hat{r}_1, \alpha, \lambda_p)} \right)^{\frac{2}{\alpha}} \right)^2}{4d^2 \hat{r}_1^2}}} \quad (3)$$

where  $T(\hat{r}_1, \alpha, \lambda_p) = 2P\pi\lambda_p \frac{\hat{r}_1^{2-\alpha}}{\alpha-2}$ , and  $\hat{r}_1$  is a solution of the following equation:  $\hat{r}_1^\alpha - \frac{2P_p\pi\lambda_p \hat{r}_1^2}{m(\alpha-2)} - \frac{P_p}{m} = 0$ .

*Proof:* Appendix.

In Proposition 1, we consider that the nearest PT has a dominant effect on the CID and approximate the distribution in terms of  $\hat{r}_1$  denoting the estimated distance between the sensor and its nearest PT. When the pathloss

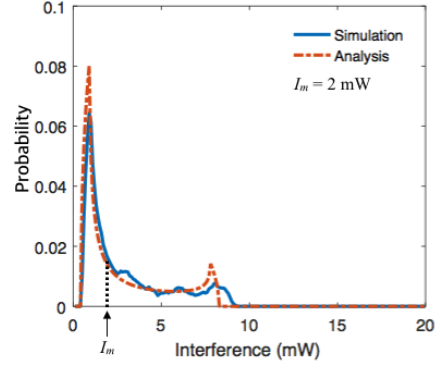


Fig. 3. The conditional interference distributions when  $I_m = 2\text{mW}$ ,  $\alpha = 4$ ,  $d = 1$ , and  $\lambda_p = 0.003$ , or 3000 PTs/km<sup>2</sup>.

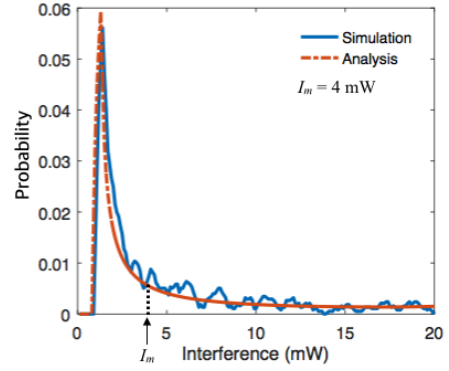


Fig. 4. The conditional interference distributions when  $I_m = 4\text{mW}$ ,  $\alpha = 4$ ,  $d = 1$ , and  $\lambda_p = 0.003$ , or 3000 PTs/km<sup>2</sup>.

exponent  $\alpha$  is 4, then the estimated distance  $\hat{r}_1$  is equal to  $\left( \frac{P_p \pi \lambda_p + \sqrt{(P_p \pi \lambda_p)^2 + 4mP_p}}{2m} \right)^{0.5}$ . The approximation of the CID (3) is tight when the PT density  $\lambda_p$  is up to 0.003, or 3000 PTs/km<sup>2</sup>. It implies that the approximation would be effective to the case that the primary network is cellular network.

Fig. 3 and Fig. 4 show two CIDs (2) with respect to the different sensor measurement  $I_m$ . The shape of CID is skewed to the left of the sensor measurement and characterized by having a long tail. Variance and skewness of the CID both increase with  $I_m$ . It implies that the actual received interference at ST  $i$  may be lower than the sensor measurement  $I_m$  with a considerable probability. In other words, there would be more transmission opportunities for STs. This phenomenon gives us an insight that STs can access the medium more aggressively while not degrading the primary communication qualities.

### III. COGNITIVE RANDOM ACCESS BASED ON CONDITIONAL INTERFERENCE DISTRIBUTION

Fig. 5 shows the snapshot of the network topology where PTs and STs are randomly located with the density of  $\lambda_p = 0.001$ , and  $\lambda_s = 0.002$ . Although the same density is applied to the network, we can observe the regional variance of the population, which makes different local interference

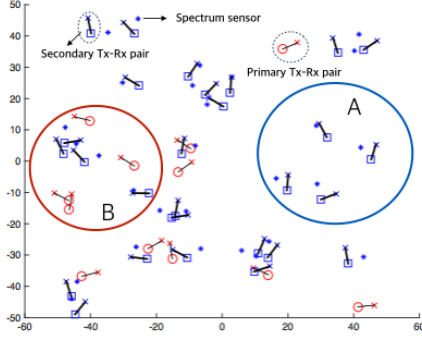


Fig. 5. A snapshot of network topology. The PT density  $\lambda_p$  is 0.001 and the ST density  $\lambda_s$  is 0.002.

conditions. The STs in subarea A are located in relatively sparse environment with low population of PTs, where the STs could access the channel without interruption. On the other hand, the STs in subarea B are located in relatively high region interference imposed by PTs, and the transmission attempt of STs in B would be obstructed.

To deal with these regional differences, we propose a cognitive random access by tuning each user's transmission probability based on the CID (3). It is worth noting that the CID gives us the probability that the aggregate interference at a ST is lower than an arbitrary threshold. Unlike the conventional ALOHA, STs have the different transmission probabilities with respect to the interference measured by the sensors.

We assume that the time is slotted and synchronized in the networks. We focus on a snapshot of the communication process, where the network topology does not change during each time slot. Each transmitter in the network always has enough data to transmit. Let us assume that the STs know the corresponding sensor location. The time delay that the ST receives interference measurement from its sensor is negligible.

#### A. Improving Area Spetral Efficiency

Our purpose is to improve the area spectral efficiency (ASE)  $\eta$ , the sum of data rates per unit bandwidth in the unit area [14], while protecting primary networks. Under a constraint of satisfying a required outage probability of primary transmissions, we determine transmission probabilities of STs  $\mathbf{p} = \{p_1, p_2, \dots, p_i, \dots\}$  in order to maximize  $\eta$  as follows:

$$(P1) \quad \max_{\mathbf{p}} \quad \eta = \lambda_s E_i[p_i] p_s \log(1 + \beta) \quad (4)$$

$$\text{subject to} \quad \Pr\{SIR_p \leq \beta\} \leq \tau, \quad (5)$$

$$0 \leq p_i \leq 1 \quad \forall i, \quad (6)$$

where  $\beta$  is a target SIR threshold, and  $p_s$  is transmission success probability of secondary user. We neglect noise in our analytical calculations. In the perspective of a typical ST, interferer density is  $\lambda_p + \lambda_s E[p_i]$ . From [15], the probability  $p_s$  can be calculated as follows:

$$p_s = \Pr[SIR > \beta] = e^{-(\lambda_p + \lambda_s E_i[p_i]) r_s^2 \left(\frac{P_p \beta}{P_s}\right)^{2/\alpha} C(\alpha)}. \quad (7)$$

where  $C(\alpha) = \frac{2\pi}{\alpha} \Gamma(\frac{2}{\alpha}) \Gamma(1 - \frac{2}{\alpha})$  and  $\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt$ . The parameter  $r_s$  is a distance between secondary transmitter and receiver. Here, we assume that the distance  $r_s$  is same for all STs and their corresponding receivers. The constraint (5) assures that the outage probability of the primary communications cannot exceed the target value.

**Proposition 2.** The optimal transmission probability  $\mathbf{p}^*$  should satisfy

$$E[p_i^*] = \max \left[ 0, \min \left\{ 1, \frac{1}{\lambda_s} \left( \frac{\ln(1/(1-\tau))}{r_p^2 \left(\frac{P_s \beta}{P_p}\right)^{2/\alpha} \frac{2}{\alpha} C(\alpha)} - \lambda_p \right) \right\} \right]. \quad (8)$$

*Proof:* From the outage probability in [17], we can represent the constraint (5) as follows:

$$\Pr\{SIR_p \leq \beta\} = 1 - e^{-(\lambda_p + \lambda_s E[p_i]) r_p^2 \left(\frac{P_s \beta}{P_p}\right)^{2/\alpha} C(\alpha)}, \quad (9)$$

$$E[p_i] \leq \frac{1}{\lambda_s} \left\{ \frac{\ln(1/(1-\tau))}{r_p^2 \left(\frac{P_s \beta}{P_p}\right)^{2/\alpha} C(\alpha)} - \lambda_p \right\}. \quad (10)$$

We can rewritten the expectation term  $E[p_i]$  of (10) as  $\frac{1}{N} \sum_i^N p_i$  without loss of generality, where  $N$  is the number of STs. Then, we can relax constraint (5) and obtain the following Lagrangian function:

$$L(\mathbf{p}, \mu) = \lambda_s E[p_i] p_s \log(1 + \beta) + \mu \left\{ \frac{N}{\lambda_s} \left( \frac{\ln(1/(1-\tau))}{r_p^2 \beta^{2/\alpha} C(\alpha)} - \lambda_p \right) - \sum_i^N p_i \right\}, \quad (11)$$

where  $\mu$  is a nonnegative Lagrangian multiplier. The Karush-Kuhn-Tucker (KKT) conditions of the problem **P1** are necessary for optimality. The KKT conditions are given as follows:

$$\frac{\partial L}{\partial p_i} = \frac{\lambda_p \lambda_s \log(1 + \beta) e^{-(\lambda_p + \lambda_s / N \sum_i^N p_i) r_s^2 \left(\frac{P_p \beta}{P_s}\right)^{2/\alpha} C(\alpha)}}{N} \times \underbrace{\left( 1 - \frac{\lambda_s}{N} \sum_i^N p_i r_s^2 (P_p \beta / P_s)^{2/\alpha} C(\alpha) \right)}_{(A)} - \mu \leq 0, \quad (12)$$

$$\frac{\partial L}{\partial \mu} = \frac{N}{\lambda_s} \left( \frac{\ln(1/(1-\tau))}{r_p^2 \left(\frac{P_s \beta}{P_p}\right)^{2/\alpha} C(\alpha)} - \lambda_p \right) - \sum_i^N p_i \leq 0, \quad (13)$$

$$p_i \left\{ \underbrace{\frac{\lambda_p \lambda_s \log(1 + \beta) e^{-(\lambda_p + \lambda_s / N \sum_i^N p_i) r_s^2 \left(\frac{P_p \beta}{P_s}\right)^{2/\alpha} C(\alpha)}}{N}}_{(B)} \right. \quad (14)$$

$$\left. \times \left( 1 - \frac{\lambda_s}{N} \sum_i^N p_i r_s^2 (P_p \beta / P_s)^{2/\alpha} C(\alpha) \right) - \mu \right\} = 0, \quad (14)$$

$$\mu \left\{ \frac{N}{\lambda_s} \left( \frac{\ln(1/(1-\tau))}{r_p^2 (P_s \beta / P_p)^{2/\alpha} C(\alpha)} - \lambda_p \right) - \sum_i^N p_i \right\} = 0, \quad (15)$$

$$0 \leq p_i \leq 1 \quad \forall i. \quad (16)$$

The variable  $\mu$  should be positive. It can be proved as follows. When  $\mu = 0$ , the variable  $p_i$  should be zero for all  $i$  since the term (B) is always positive. Then, the term (A) always has a positive value, and makes the partial derivative  $\partial L / \partial p_i$  positive. It does not satisfy the condition (12). Therefore,

$$\sum_i^N p_i = \frac{N}{\lambda_s} \left( \frac{\ln(1/(1-\tau))}{r_p^2 \left( \frac{P_s \beta}{P_p} \right)^{\frac{2}{\alpha}} C(\alpha)} - \lambda_p \right), \quad (17)$$

and the variable  $\mu$  is positive and equal to the term (B). ■

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**Algorithm 1** Cognitive Random Access

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**Require:**  $\lambda_p$ ,  $\lambda_s$ , and  $I_{th}$

- 1: **Spectrum sensor:**
- 2: Measure the aggregate interference  $m_i$
- 3: **Secondary transmitter:**
- 4: Get  $m_i$  from the spectrum sensor
- 5: Compute a probability  $F_{I;m_i}(I_{th})$  for  $m_i$  using (3)
- 6:  $w_i \leftarrow F_{I;m_i}(I_{th})$
- 7: Calculate an expectation  $E[p_i^*]$

$$E[p_i^*] \leftarrow \max \left[ 0, \min \left\{ 1, \frac{1}{\lambda_s} \left( \frac{\ln(1/(1-\tau))}{r_p^2 \left( \frac{P_s \beta}{P_p} \right)^{\frac{2}{\alpha}} C(\alpha)} - \lambda_p \right) \right\} \right]$$

- 8:  $p_i \leftarrow \min \left[ 1, \frac{w_i}{E[w_i]} E[p_i^*] \right]$
  - 9: Go line 2
- 

The Proposition 2 determines only the expectation  $E[p_i^*]$  of the optimal transmission probability  $p_i^*$  in the network, but it cannot find the optimal  $p_i^*$  for each ST  $i$ . Instead, we can combine (3) in Proposition 1 and (8) in Proposition 2, in order to make an algorithm finding a suboptimal  $\hat{p}_i$ .

We propose a simple algorithm to find  $\hat{p}_i$  that satisfies the necessary condition (8). Let  $w_i$  be a probability weight factor for ST  $i$ . The transmission probability  $\hat{p}_i$  is determined as follows:

$$\hat{p}_i = \min \left[ 1, \frac{w_i}{E[w_i]} E[p_i^*] \right], \quad (18)$$

Here, the cumulative CID  $F_{I;m_i}$  determines the factor  $w_i$  in the following manner.

$$w_i = F_{I;m_i}(I_{th}), \quad (19)$$

where  $m_i$  is a measured interference by the sensor adjacent to the ST  $i$ , and  $I_{th}$  is a given interference threshold. The weight  $w_i$  means the probability that the ST  $i$  receives an aggregate interference lower than the threshold  $I_{th}$ . In (18), the normalized probability  $w_i / E[w_i]$  adjusts a chance of spectrum access. For example, as shown in Fig 5, the STs in sparse environment like area A may have a high weight  $w_i$ . The whole process of the proposed cognitive random access is described in Algorithm 1.

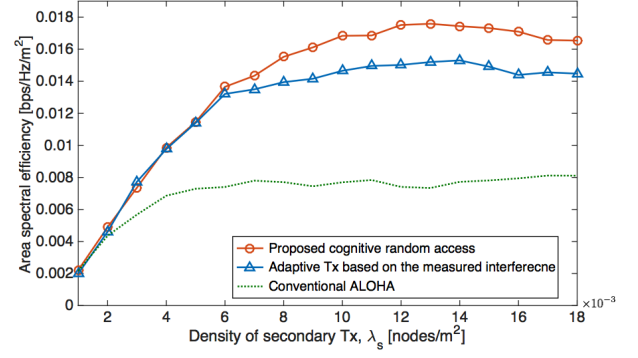


Fig. 6. ASE as a function of secondary transmitter density ( $\lambda_p = 0.001$ ,  $\beta = 3$  dB,  $\tau = 0.05$ ,  $d = 1$ ).

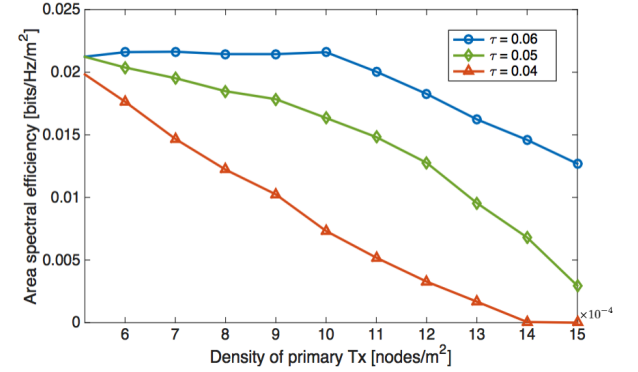


Fig. 7. ASE as a function of primary transmitter density with various  $\tau$  ( $\lambda_s = 0.01$ ,  $\beta = 3$  dB,  $d = 1$ ).

## B. Performance Evaluation

We evaluate the proposed random access scheme through 1,000,000 simulations. At every simulation, PTs and STs are independent and identically distributed according to a homogeneous PPP with intensity  $\lambda_p$  and  $\lambda_s$ , respectively, in a  $100 \text{ m} \times 100 \text{ m}$  area. Spectrum sensor is located at a distance of  $d$  from the corresponding ST. The communication distances of primary and secondary pairs is 3 m. The distance between the ST and its adjacent sensor is set to 1 m. The interference threshold  $I_{th}$  is set to 2 dBm. The primary and secondary transmission powers are 23 dBm and 5 dBm, respectively. We set the noise power as -70 dBm and consider Rayleigh fading.

Fig. 6 shows ASE performance as a function of the ST density  $\lambda_s$ . The proposed scheme surpasses the conventional ALOHA scheme. Also, we conducted the comparison with adaptive transmission that deterministically attempts to send data when the measurement of an adjacent sensor is lower than an interference threshold. The proposed scheme shows better ASE performance than the other schemes for high density of ST  $\lambda_s$ . This ASE difference comes from the probabilistic transmission based on the CID (3), which gives us a probability that actual received interference at ST may be lower than the measurement. With this information, the ST attempts to access the spectrum more aggressively, producing higher ASE. Also, we observe ASE performance of the proposed scheme

with respect to the PT density  $\lambda_p$  as shown in Fig. 7. When the primary outage probability constraint  $\tau$  is small, ASE is sensitive to  $\lambda_p$ .

#### IV. CONCLUSION

This paper focuses on cognitive radio (CR) based IoT networks where multiple sensors are deployed to monitor interference temperature in the area. An inherent characteristic of this CR network induces the different spectrum occupancy at the locations of the CR IoT devices and the sensors. To compensate this difference, we derive a conditional interference distribution (CID) at the CR device for a given measured interference at the sensor. We find that the shape of the CID is a left-skewed distribution. This statistic property implies that an actual received interference at CR device may be lower than the sensor measurement with a considerable probability. Reflecting this phenomenon, we devise a cognitive random access scheme which adaptively adjusts transmission probability with respect to the CID. Our scheme improves area spectral efficiency compared to conventional ALOHA and threshold based random access protocol, where an IoT device can access the medium only when a measured sensor value is lower than the predetermined threshold.

#### V. APPENDIX: PROOF OF PROPOSITION 1

The measured aggregate interference  $I_m$  at the sensor can be decomposed as follows:

$$I_m = I_{x_1} + I_{\sum_{\Phi_p \setminus \{x_1\}}}, \quad (20)$$

where  $I_{x_1} = Pl(o, r_1)$ ,  $x_1$  is the nearest PT from the sensor, and  $r_1$  is the distance between the sensor and PT  $x_1$ . Since spectrum sensors measure interference for a enough time duration, the fading effect can be averaged out in the measurement. We assume that sensors are close to STs enough to consider PT  $x_1$  as a common dominant interferer for both the sensor and ST  $i$ . Now then, we investigate how these two sets of interferers have an influence on the ST  $i$ . First, PT  $x_1$  imposes an interference  $I_{x_1}$  to ST  $i$  as  $I_{x_1} = P(r_1^2 + d^2 - 2r_1d \cos \theta)^{-\alpha/2}$ . For a fixed interference  $Pr_1^{-\alpha}$ , the angle  $\theta$  determines interference strength  $I_{x_1}$ . As  $\theta$  increases, the interference  $I_{x_1}$  decreases by  $\cos(\theta)$ . Using this geometric property, we can transit the cumulative CID function  $F_{I;m}(x) = \Pr\{I \leq x | I_m = m\}$  to the probability with respect to  $\theta$  as follows:

$$\Pr\{\theta \geq \theta_x | I_m = m\} = 1 - \frac{\theta_x}{\pi} \quad (21)$$

$$= 1 - \pi \cos^{-1} \left( \frac{r_1^2 + d^2 - \left( \frac{P}{x - \sum_{\Phi_p \setminus \{x_1\}} Pl(o, r_i)} \right)^{\frac{2}{\alpha}}}{2r_1d} \right). \quad (22)$$

Here, we use an approximation that interference  $I_{\sum_{\Phi_p \setminus \{x_1\}}}$  at ST  $i$  from PTs in  $\Phi_p \setminus \{x_1\}$  is equal to mean interference  $E[I_{\Phi_p \setminus \{x_1\}}] = \lambda_p \int_0^{2\pi} \int_{r_1}^{\infty} Pl(o, r) r dr d\phi = 2P\pi\lambda_p \frac{r_1^{2-\alpha}}{\alpha-2}$ . Let  $\hat{r}_1$  denote the estimated distance from the nearest PT. For a given  $I_m$  equal to  $m$  in (20), we can find the estimated distance  $\hat{r}_1$  which is the solution of the following equation:

$m = P\hat{r}_1^{-\alpha} + 2P\pi\lambda_p \frac{\hat{r}_1^{2-\alpha}}{\alpha-2}$ . Now, then we can specify the cumulative CID  $F_{I;m}(x)$ , of which derivative is the CID function  $f_{I;m}(x)$  (3).

$$\begin{aligned} \frac{d}{dx} & \left\{ 1 - \pi \cos^{-1} \left( \frac{r_1^2 + d^2 - \left( \frac{P}{x - 2P\pi\lambda_p \frac{\hat{r}_1^{2-\alpha}}{\alpha-2}} \right)^{\frac{2}{\alpha}}}{2r_1d} \right) \right\} \\ &= \frac{\frac{P_p}{\pi d \hat{r}_1 \alpha (x - T(\hat{r}_1, \alpha, \lambda_p))^2} \left( \frac{P_p}{x - T(\hat{r}_1, \alpha, \lambda_p)} \right)^{\frac{2}{\alpha}-1}}{\sqrt{1 - \frac{\left( \hat{r}_1^2 + d^2 - \left( \frac{P_p}{x - T(\hat{r}_1, \alpha, \lambda_p)} \right)^{\frac{2}{\alpha}} \right)^2}{4d^2 \hat{r}_1^2}}}, \end{aligned} \quad (23)$$

where  $T(\hat{r}_1, \alpha, \lambda_p) = 2P\pi\lambda_p \frac{\hat{r}_1^{2-\alpha}}{\alpha-2}$ . ■

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